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IMPLICIT INTUITION BASIC RESEARCH CHALLENGE (I2BRC)

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Overview

This report summarizes a set of research studies supported by a Basic Research Challenge to examine how implicit learning research can be used to accelerate the development of expert intuition in training (Implicit Intuition Basic Research Challenge; I2BRC). The foundational basic science approach to this work is that implicit learning (Reber, 2013) reflects a separate type of learning and memory which accumulates through experience outside of awareness and influences behavior through intuition. From this perspective, expert intuition reflects years of implicit learning in the field which leads to nonconscious knowledge structures that support accurate intuitions, hunches and feelings that contribute to highly expert performance. Implicit knowledge is not available to report making it impossible to teach in the classroom and often quite difficult to extract from experts who use it successfully. Phenomena of implicit learning are often studied in laboratory conditions with novel, artificial tasks. The main goal of the research project described here is to examine how to take capitalize on these laboratory paradigms to accelerate the development of operationally relevant intuitive decision making in practical contexts.

The first set of projects began as part of a multi-site research initiative to examine the Neurocognitive Foundations of Implicit Intuition. Three neuroimaging studies are described that were carried out by researchers at Northwestern University. The main findings are summarized together with a list of scientific presentations, publications and graduate student training milestones. In 2016, the aims were adjusted to focus on the development of a testbed for assessing implicit intuition and the development of a novel paradigm for quantifying intuitive decision making, Terrain Categorization. Research supported in this line of work adapted previously studied paradigms for implicit learning in visual categorization to develop a new research protocol inspired by Land Navigation training. The set of studies examining that idea are described here as part of a two-year effort, Enhancing Intuition Through Implicit Learning (Jan 2016 – Dec 2017, NCE through Dec 2018). Across studies, these research projects identified methods for applying laboratory studies of implicit learning to the development of intuitive expertise but consistently identified challenges in accelerating the development of intuition to a level of robust detectability within a 1-2 hour experimental session. As a general recommendation, implicit learning techniques can likely be applied to accelerating the development of intuition across longer training protocols. Establishing this hypothesis will be best done within research approaches that are closely tied to tasks based on operationally relevant training rather than laboratory paradigms designed around novel, arbitrary, carefully controlled stimuli.

Research supported by the Neurocognitive Foundation part of the project has led to substantial scientific output, including 6 manuscripts published or in preparation and 14 conference presentations, 1 completed Doctoral Dissertation (Hectmann), 1 completed Masters Thesis (Reuveni, Ph.D. thesis underway) to date. Data analysis and preparation of reports of findings are still underway and we expect at least 3 more manuscripts to be published in peer-reviewed journals.

1. Neurocognitive Foundations of Implicit Intuition

Three projects sought to examine the neurocognitive foundation of intuition and intuitive decision making using theoretical ideas and paradigms used laboratory studies to examine the operation of implicit (nonconscious) learning and memory. Each of these projects was based on using functional magnetic resonance imaging (fMRI) to characterize the neurocognitive foundations of these basic processes.

1.1 Insight Problem Solving

When solving a complex problem by insight, the subjective experience of the solver is often that of being stuck without obvious progress and then a sudden “Aha!” moment where the answer springs to mind unexpectedly. The lack of awareness of the impending solution indicates that implicit processing is occurring outside awareness that is leading to the discovery of the solution. This process has been extensively studied (Kounios & Beeman 2015) to understand how this process influences complex decision making and creativity. In our prior research using neuroimaging, we identified the importance of the right temporal lobe in the neural activity that precedes the moment of insight (Jung-Beeman et al., 2004). In the current study, we sought to identify factors that would contribute to enhancing the probability of a successful insight event.

Laboratory studies have shown that an effective paradigm for creating moments of insight is the Compound Remote Associates Task where participants attempt to find a word that links three seemingly unrelated words (e.g., Pine-Sauce-Crab; solution is ‘apple’). While performing this task while neuroimaging data were collected (fMRI), participants were primed before each problem with a task directing attention either globally or locally. In Figure 1.1.1., neural regions in the medial prefrontal cortex were found to be activated by both directing attention globally and neural activity immediately preceding insight.

This result suggests that manipulating the focus of attention globally might increase the tendency for an insight-solution event to occur. Directing a problem-solver’s attention to the “forest instead of the trees” might increase the degree to which implicit and intuitive processes affect problem solving or decision-making.

Testing this idea in a more operationally relevant task would require development of a decision-making testbed that blends the control of laboratory protocols with decisions more related to real-world contexts.

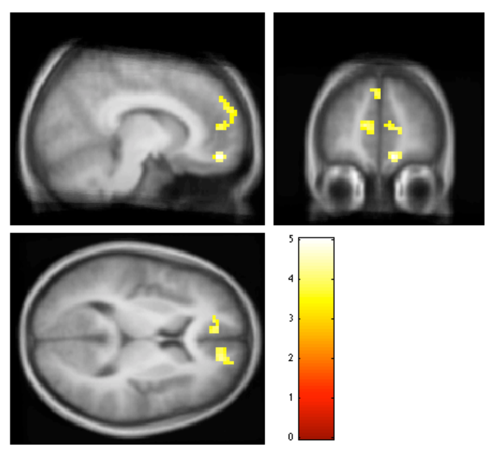

Figure 1.1. Overlapping regions in prefrontal cortex associated with global focus of spatial attention and solving problems by insight.

1.2 Implicit Recognition

The second area of investigation into the neurocognitive foundations of implicit-intuitive decision-making was built on a phenomenon of "implicit recognition" described by Voss & Paller (2009). In this paradigm, participants are exposed to novel abstract visual images but with attention directed away from the stimuli during a brief exposure. As a consequence of this presentation method, participants can sometimes enter a state of *high-accuracy guessing*. When this occurs, participants report a subjective sense of no memory for the studied stimuli but when asked which of two they recognize as having seen before, are able to pick the correct image out at a rate much higher than chance. This phenomenon reflects a common way in which implicit memory for prior experience is expressed (Reber 2013) and is used here as a model of intuition under the idea that the guesses made by participants reflect a similar process to an intuitive hunch.

The paradigm used here attempted to create the high-accuracy guessing state using an approach of *value directed recognition* (VDR). In this paradigm images are designated as high or low value for a future memory test. Participants typically report directing attention to the high-value items over low-value items. Later, the low-value items can exhibit this guessing effect, as seen in the left columns on Figure 1.2, Panel A. When reporting no confidence in their answer, participants were still accurate 60% of the time (50% is chance).

We sought to identify the neural correlates of this phenomenon with fMRI, however, within the scanning environment, we did not observe the high-accuracy guessing phenomenon. This is one of the challenges of studying implicit and intuitive processes in the laboratory. It can be hard to create moments of intuition on cue for study. The data obtained did bring some significant insight into basic memory processes, Figure 1.2, Panel B.

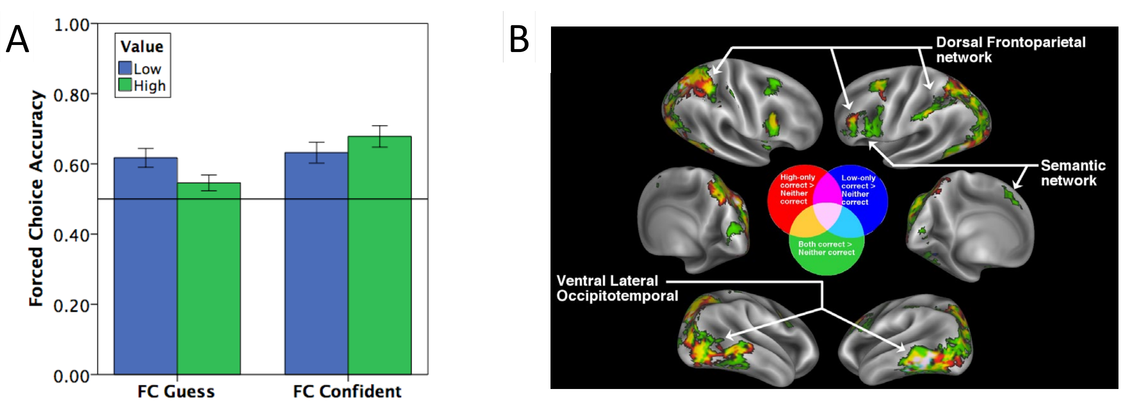

Figure 1.2. (A) Memory performance on a forced-choice recognition test (FC). When pilot participants reported guessing the answer, they did better for 'low-value' items than high-value items. (B) Activity associated with successful memory in a subsequent memory test showing increased activity for successful memory in three networks: dorsal frontoparietal (cognitive control), ventral-lateral occipito-temporal (visual object processing) and parietal semantic cortical areas.

A manuscript (Cohen, Cheng, Paller & Reber, in press) has just been accepted for publication that focuses on increased neural activity within the reward regions of the brain during successful memory as well as neural activity with strategic control of memory. Of note, the reward system activity does not appear to be selectively directed consciously, suggesting that feedback and reward are likely to play an important role in the creation and use of more intuitive modes of thought. A second manuscript is also in preparation that examines interactions between accuracy and confidence in memory reflected in visual system neural activity.

1.3 Modeling Implicit/Explicit Memory System Interactions

The third neuroimaging approach to examining implicit intuition directly addressed the challenges of eliciting intuitive approaches using computational modeling methods to attempt to better characterize mental states during a complex learning process. We had previously described a computational model, PINNACLE (Parallel Interaction Neural Networks Active during Category Learning) that provides a model of the interaction between implicit and explicit processes during learning (Nomura & Reber, 2012). In the current approach, we further extended this modeling system to incorporate more a more sophisticated model of reward-based processing and more complex conscious hypothesis testing mechanisms. PINNACLE 2.0 (Figure 1.3; Reuveni, unpublished Master's thesis) was then used to fit the learning process during a laboratory paradigm in which participants were first encouraged to use a simple conscious rule, and then gradually learn that this rule was inaccurate and must be abandoned in favor of an implicitly learned rule. The strategy use of participants was inferred through

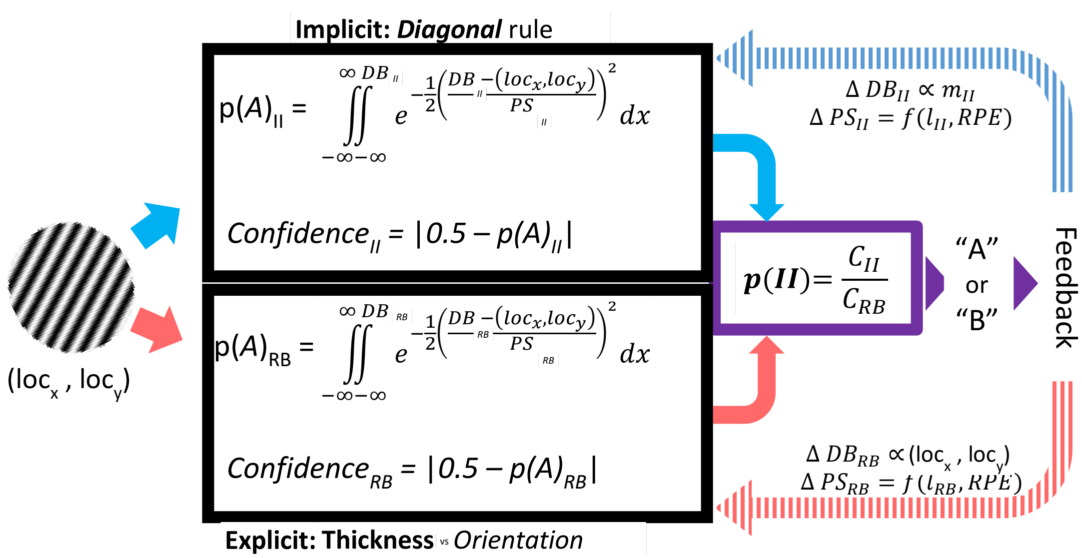

Figure 1.3. The PINNACLE computational model of implicit and explicit parallel learning systems and their interactions during learning that leads to switching between strategies.

modeling with PINNACLE 2.0 yoked to the specific choice behavior of the participants to predict which strategy drove response choice on each trial.

Extensive pilot testing demonstrated the difficulty of getting participants to go through the process of abandoning an initially successful rule in favor of a more intuitive approach. One aspect of why this is challenging is likely that this is normally a process that occurs very gradually over the acquisition of expertise and we are attempting to move through this process within a single hour of practice. To achieve this accelerated switch to more intuitive decision making, we used the PINNACLE 2.0 model as a kind of adaptive tutor to select stimuli so as to encourage more implicit knowledge during performance. This led to a successful round of pilot testing (Figure 1.3.2, Panel A). However, the same protocol implemented in the scanner, led to a surprising level of non-learning in participants, almost half never achieved better than chance performance.

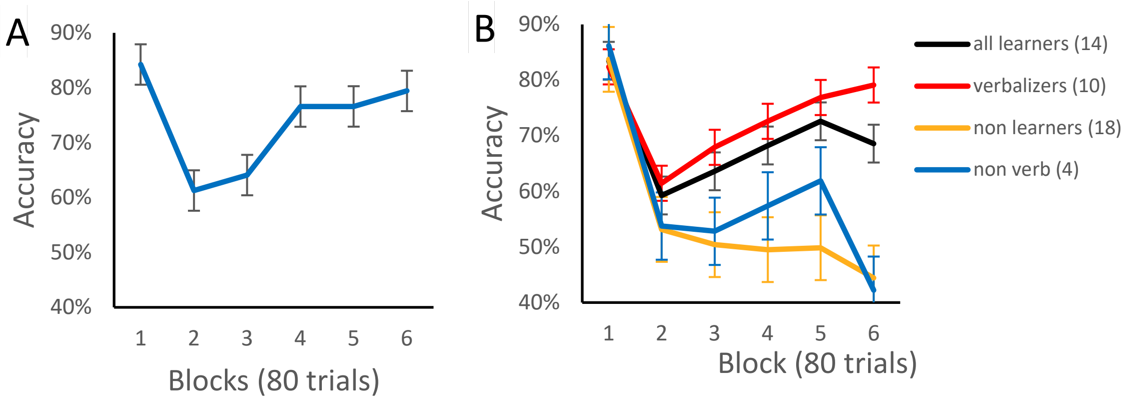

Figure 1.4. Categorization accuracy over the course of learning. (A) Pilot data (n=19) of learning guided by the PINNACLE tutor in the laboratory. (B) Data from participants obtained in the fMRI scanning environment in which many participants did not exhibit learning during the task.

Analysis of the fMRI is underway and will likely still provide insights into neural activity associated with learning (and also non-learning in the face of corrective feedback on each trial). We hypothesize that participants who are not learning well are likely rapidly cycling between ineffective strategies. We may be able to track this process with the PINNACLE 2.0 framework to identify critical aspects of the decision process to select for analysis.

1.4 Summary of Neuroimaging Studies

The three sets of studies aimed to examine the neurocognitive foundations of implicit learning applied to intuitive decision making each produced significant contributions to the fields of implicit learning and insight problem solving. The results of these studies have been reported at scientific conferences for Cognitive Neuroscience research and several manuscripts are in preparation and/or under review for publication. A common set of limitations were identified across these research areas raising challenges for developing more direct applications to improved training methods to accelerate the development of intuitive decision making for more operationally relevant domains. First, the tasks used were exclusively laboratory tasks for models of implicit (intuitive) learning and memory. Second, even with these well-controlled tasks, it is difficult to reliably elicit robustly intuitive behavior within the first hour of learning in an experimental session. Expert intuition is more commonly acquired over extended training in the field with many hours (hundreds or thousands) of experience. Select implicit learning tasks can produce behavior for which performance exceeds what can be verbally reportable, but these tasks often have very specific, restricted properties. Typically, key elements of the information to be learned have to be covertly embedded so that conscious, explicit decision making does not drive behavior. In Section 2, we report a series of experiments in which we covertly embedded structural information in a novel categorization task designed to bear more surface similarity to operationally relevant decisions that might be encountered in Land Navigation training.

2 Enhancing Intuitive Decision Making through Implicit Learning

This section reports on the results of a project following on the prior research examining the neurocognitive foundations of implicit learning as it contributes to intuitive decision making. A new approach was developed to create a more operationally-relevant learning task in which the effects of implicit learning and intuitive decision making could be quantified (Smith et al. 2017). With an effective testbed for measuring the impact of implicit knowledge, it was expected that approaches for accelerating the development of intuition could be developed and tested.

The new paradigm was developed based on existing laboratory tasks for *category learning*. The category learning research domain involves showing participants a number of novel stimuli that they must learn to correctly label as in one of a small number of possible categories (typically A/B or A/B/C). This can be accomplished with no information provided to the participants about the category structure or correct answers and participants learn the categories based on feedback on each trial. Early in learning, responses are based on guesses but as more trials are seen and completed, the prior answers and feedback about the correct answer allow participants to develop knowledge of the task structure.

In most laboratory versions of the category learning paradigm (c.f., Nomura & Reber 2008), the stimuli to be learned are artificial and vary on a few arbitrary dimensions, e.g., sine wave gratings that vary in frequency (stripe thickness) and orientation (tilt). These paradigms have been a powerful tool to study the basic science of learning and characterize the contributions of separate underlying implicit and explicit memory systems (Ashby et al. 1998; Nomura et al. 2007). In addition, this paradigm can be taken as a model of decision-making since the label selection response is effectively a decision about the category membership of a stimulus that has to be made on partial, incomplete information.

Decisions to be made about the local terrain environment was the domain selected for the development of our model task. Working with Charles River Analytics (PI: Dr. James Niehaus), a procedural terrain generator was developed within a simulation framework that varied on four specified dimensions: ground topology (hilliness), vegetation density, weather conditions and time of day. The terrains generated this way provided a model of decision tasks in which a course of action to be taken depends on the environmental characteristics (e.g., patrolling, route selection, force placement). To examine a learning process using these stimuli, we embedded a covert and arbitrary category structure on these stimuli that had to be discovered by participants. The results of several studies examining learning of the Terrain Categorization task are reported here.

General Methods

For the Terrain Categorization task, the underlying terrains were procedurally generated according to a set of 4 environmental parameters that controlled: (1) the topographic structure ("hilliness"), (2) density of vegetation (trees and bushes), (3) weather conditions and (4) time of day. Each of these parameters varied continuously across a range from zero to one with higher values being more hills, more vegetation, more weather (clouds, fog, rain) or later in the evening (noon to sunset). Specific terrains were generated pseudo-randomly after specification of values for these four parameters, meaning a very large number of different terrain stimuli could be created with this algorithm (Figure 2.1).

Figure 2.1: Example of Category Bravo stimuli (left panel). Characteristics of Bravo include steep topology, time of day of late afternoon, and clear weather. Prototype values: 0.937, 0.347, 0.863, 0.224. Example of Category Charlie (right panel). Characteristics of Charlie include medium topology, time of day of early morning, and cloudy weather. Prototype values: 0.609, 0.446, 0.592, 0.567.

The participants' experience with a terrain was based on a video clip of simulation-based movement through the terrain from a first-person perspective. The location of the point within the terrain for movement was chosen randomly and the movement was forward (an S-shaped curve to provide information about the terrain environment to the left and right was added for Exp 2). The videos were 4 seconds long and were observed by the participants while they were trying to accomplish the learning goals of the task.

Participants were told that they were in charge of delivering supplies during a mission on an alien planet. For this mission, a travel method needed to be chosen in order to deliver needed supplies to settlement building teams. In response to a 4s video clip, participants attempted to select the correct travel method for successful deliveries for that terrain environment. The three choices were labeled simply as Alpha, Bravo, Charlie (A/B/C), and no information about how to identify the correct label from the terrain was provided. The video clip was followed by a short response period for the participants to select their choice. After selection, feedback (visual and auditory) was provided about the accuracy of their choice and the correct answer (if necessary).

Over the course of the training session (typically 1 hour with 150-450 trials), participants attempted to learn the correct response for each video, which entailed building an understanding of the hidden category structure. The correct answer for each terrain was determined using 3 hidden prototypes defined by specific values across the 4 parameters. The closest prototype to the presented stimulus defined the correct answer for the trial. The stimuli were generated to have a mathematically characterized structure determined by distance to the prototypes. As is common in prototype-category learning experiments, the individual unique stimuli never had exactly the values of the prototypic member, but instead had each parameter slightly randomly adjusted (jittered) to maintain a target "distance" from this central value in the perceptual stimulus space. The stimuli for each of the three categories were effectively within a 4d-hypershell around the prototypes. This mathematical construction allows for varying the difficulty of the task by increasing the distance from each stimulus to the prototype (reducing within-category difficulty) or changing the distance between the categories (increasing or reducing across-category difficulty).

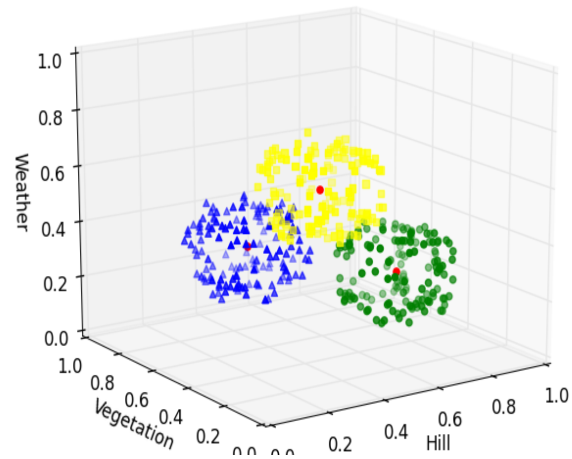

Figure 2.1: Schematic of prototype category stimulus organization within the 4 visual dimensions (3 shown: topology, vegetation, weather). Red center dots represent prototype values. Blue, yellow, and green dots represent exemplar values used to generate stimuli for each category.

Following the task, a post-session interview was administered in order to assess the extent to which participants used explicit knowledge to successfully categorize the terrain videos. For several experiments (Experiments 1, 6, and 7), participants were asked a simple, open-ended question: describe your experience completing the task. Interviews for the remaining experiments contained additional questions about the importance of visual features to their decision-making (Experiments 2-5), and how the importance of visual features varied across categories (Experiment 5).

2.1 Experiment 1

In a first experiment, we demonstrated that participants could successfully learn the novel category structure with stimuli based on the mathematical prototype structure but rendered as first-person perspective moving through the terrain environment.

Participants. Eleven participants were recruited for this experiment recruited from the NU community and paid ($15/hr) for their participation. All experimental protocols and procedures were reviewed and approved by the NU Institutional Review Board.

Materials. For Experiment 1, the prototype values for the three categories were (in order of hilliness, vegetation, time of day and weather; [0-1]): Alpha (0.3, 0.4, 0.3, 0.3), Bravo (0.4, 0.1, 0.7, 0.4), Charlie (0.1, 0.3, 0.5, 0.7). The between-category distance was set to 0.5 and the within-category distance was set to 0.141. Each video contained simulated movement characterized as a straight line forward through the environment.

Procedure. Participants were provided with the 'alien world' cover story and instructed they would be learning from trial-and-error with feedback. The experimental session included 150 trials of learning with feedback with self-terminated breaks every 50 trials. Trials were pseudo-randomized by block so that trials belonging to a particular category would not appear more than three times consecutively. After completing the task, participants were given a short, open-ended interview during which they were asked to describe their experience performing the task. Participants were also asked to report any categorization strategies as well as at what point during the task they began using these strategies.

Results. Participants successfully learned the correct categories over the course of the session (Figure 2.3) with response accuracy reaching 81% correct (SD=21%), reliably better than chance (33%), $t(10) = 7.44$, $p<0.001$. Final block performance was reliably higher than first block performance (M=56%, SD=11%), $t(10)=3.67$, $p<.005$. However, the high level of initial performance in the first block suggested the possibility that participants were rapidly identifying a single feature to use for categorization. In the post-session interviews, participants reported that the Charlie category was quite distinctive by the weather, which included rain (appearing only when the Weather dimension was at 0.6 or greater) that was noticed immediately and explicitly during learning.

Discussion. Although successful learning was observed, the data did not rule out the possibility that participants only learned the simple association from Category Charlie to the presence of rain. In Experiment 2, upgrades to the stimulus generation software allowed for improvements to the experimental protocol to attempt to identify parameters that would elicit gradual and even learning across categories typical of more implicit learning.

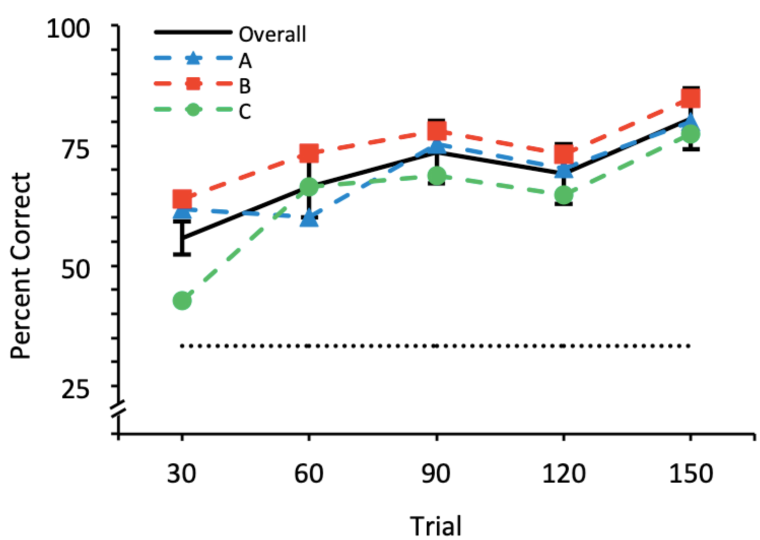

Figure 2.3: Overall and category accuracy in Experiment 1. 150 total trials were used in this task. Percent correct was determined by measuring performance across blocks of 30 trials. Participants showed learning over the course of the task, but participants showed lower performance on Category Charlie compared to Alpha and Bravo. Overall performance was greater than chance (33%, represented by the dotted line) during the final block.

2.2 Experiment 2

For Experiment 2, the implementation of the weather dimension was adjusted to make the changes in weather more gradual across the allowable values on this dimension (visible rain was removed). In addition, upgrades to the stimulus generation software allowed for generation of more fine-grained parameter values (to several more significant digits) and greater control over the first-person camera trajectory.

Participants. Nineteen participants were recruited from the NU community and paid $15/hr for participation.

Materials. New videos were rendered with the upgraded software. The prototype values for the three categories were (in order of hilliness, vegetation, time of day and weather; [0-1]): Alpha (0.124, 0.110, 0.148, 0.307), Bravo (0.377, 0.471, 0.079, 0.531), Charlie (0.580, 0.209, 0.313, 0.239). The same within-category variance structure as in Experiment 1 was used. **T**he path of movement through the simulated environment was changed from a straight line to a backwards “S” in order to provide more opportunities to perceive visual features in the environment to the left and right of the viewpoint.

Procedure. Based on the time participants took to complete the session in Experiment 1, the protocol in Experiment 2 was lengthened to 300 trials. As in Experiment 1, the alien worlds cover story was used to explain the learning goals. The post-session interview was substantially expanded to identify the explicit strategies used by the participants. After asking the participants to describe their experience completing the task, the experimenter posed the question, *“Let’s say a good friend is coming in tomorrow to complete the same discrimination task you just completed and you want to give them a leg up. What would you tell them to ensure that they would be able to successfully discriminate between Alpha, Bravo, or Charlie?”* In addition, participants were asked to report the importance of each of the four feature dimensions to their decision-making using 1-10 Likert scales. Finally, participants were then asked whether each feature corresponding to low, medium, or high values in each category.

Results. Participants’ performance (Figure 2.4) increased reliably from the 38% correct (SD=9.6%) on the first block to 56% correct (SD=17%) on the final block, $t(18) = 4.87$, $p < 0.001$, indicating successful learning. However, participants reported being able to explicitly identify the Bravo category again by the distinctive weather value. Performance on the Bravo trials was significantly higher than the Alpha or Charlie trials (*t*s>2,15, *p*s<.05), raising concerns that participants had only learned that category (i.e., report Bravo if identified and guess otherwise).

Discussion. Although participants again showed improved categorization accuracy with practice, discriminability remained uneven across all three categories due to the presence of salient cues for one category.

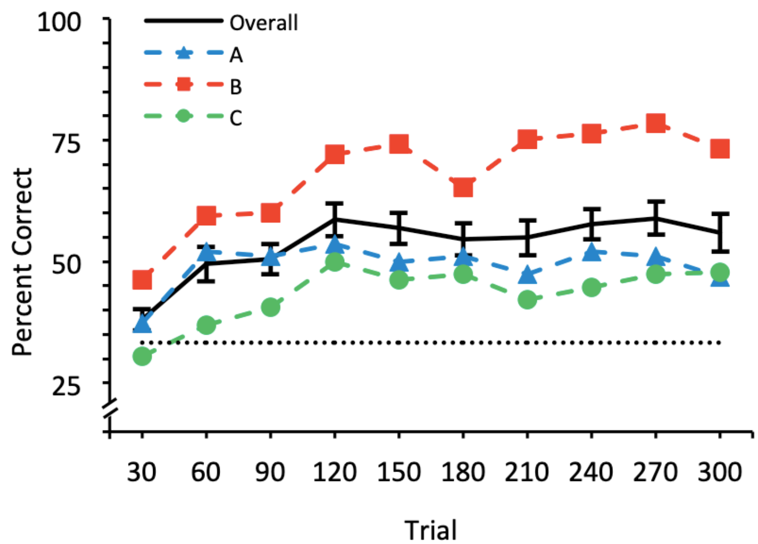

Figure 2.4: Overall and category accuracy in Experiment 2. 300 total trials were used in this task. Percent correct was determined by measuring performance across blocks of 30 trials. Participants showed learning over the course of the task, but participants showed greater performance on Category Bravo compared to Alpha and Charlie. Overall performance was greater than chance (33%, represented by the dotted line) during the final block.

2.3 Experiment 3

For Experiment 3, a new prototype category structure was created and new stimuli were generated with the intention of evenly balancing discriminability across the three categories.

Participants. Twenty-four participants were recruited from the NU community and paid $15/hr for participation.

Materials. The prototype values for the three categories were (in order of hilliness, vegetation, time of day and weather; [0-1]) were: Alpha (0.891, 0.887, 0.390, 0.582), Bravo (0.737, 0.912, 0.701, 0.224), Charlie (0.476, 0.857, 0.290, 0.324). In addition, the within-category distance was also expanded from 0.140-0.141 to 0.200-0.201 in order to encourage implicit learning over the utilization of explicit rules.

Procedure. The experimental protocol was extended to 450 trials, which could still be completed within the one-hour session. The extended post-session interview was the same as in Experiment 2. However, naïve (i.e., blind to the experimental hypothesis) raters were employed to evaluate the interviews and provide quantitative assessments of the quality of the strategic information provided by the participants. The raters were asked to score the interviews in order to assess the use of rules, conjunction scores, and articulation scores. The 'articulation' score reflected clear and articulate statements about how the dimensions related to the learned categories. After viewing the interview collected from each participant, the rater would choose a number between 1 and 10 that reflected the ability of the subject to clearly articulate the rules that they used to complete the task. In addition, a 'conjunctive' score counted distinct, accurate statements about the role of each dimension for each category with a maximum score of 12 (3 categories, 4 dimensions). The 'conjunctive' score was averaged across both the open-ended portion of the interview and the question asking participants to give advice to a friend completing the task. Four naïve raters applied the scoring rubric to each participant's interview data and the raters' scoring was highly consistent (Intraclass Correlation Coefficient, ICC = .92 for conjunctive scores; ICC = .74 for articulation).

Based on their interview responses, participants were grouped into three levels in order to determine the amount of explicit knowledge utilized during the task. A "Low" explicit knowledge group included participants who scored less than 5 on the articulation score or less than 3 on the conjunctive score. A "Moderate" explicit knowledge group scored less than 6 on the articulation score and less than 5 on the conjunctive score. The "High" explicit knowledge group scored greater than 6 on articulation score or greater than 5 on conjunction score.

Results. Participants' performance (Figure 2.5) again improved reliably across the training session, increasing from 39% (SD 9.1%) on the first block to 62% (SD 25%) on the final block, $t(23) = 5.17$, $p < 0.001$. Performance was broadly similar across the three categories, indicating that participants were not learning to rely on a single dimension to identify one of the categories. However, as in previous experiments, performance on the first block was still significantly above chance, $t(23) = 2.86$, p < 0.01, and this rapid learning suggested the possibility of some reliable on quickly discovered explicit strategies.

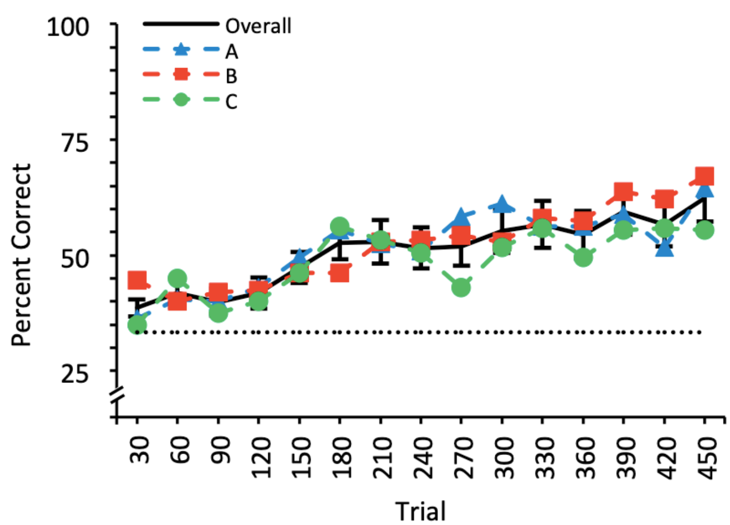

Figure 2.5: Overall and category accuracy in Experiment 3. 450 total trials were used in this task. Percent correct was determined by measuring performance across blocks of 30 trials. Participants showed learning over the course of the task. Participants showed similar levels of performance across all three categories. Overall performance was greater than chance (33%, represented by the dotted line) during the final block.

Participants belonging to the “High” explicit knowledge group showed better performance (M = 62.49%, SD = 22.55%) than participants belonging to the “Low” group (M = 45.20%, SD = 22.23%), indicating that explicit knowledge contributed at least somewhat to performance. Participants belonging to the “Moderate” group performed as well as the “High” explicit knowledge group (M = 66.76%, SD = 21.87%), suggesting that explicit knowledge did not solely account for performance.

Discussion. In Experiment 3, successful gradual learning of all three categories was observed over the course of the task. Approximately a third of the participants in Experiment 3 exhibited a profile consistent with implicit learning in which high levels of decision accuracy occurred with low explicit knowledge. The following Experiments were conducted with the goal of increasing participants’ reliance on implicit learning by adding additional probabilistic cues to the correct answer to the stimuli. Specifically, unobtrusive auditory cues predictive of the correct decisions were added to some decision trials. We hypothesized that these cues would influence decision-making by evoking a hunch about the correct answer when the cues were available. In this case, the impact of these hunches could be quantitatively measured (by increase in accuracy compared to when the cues were not available) as a model of learning intuitive decision-making.

2.4 Experiment 4

Auditory information was added to the video clips and therefore provided to participants during learning. The sound track included irrelevant sounds into which were embedded unobtrusive auditory cues predictive of the category structure. The predictive cues were added probabilistically to a subset of trials. These auditory cues were presented in the form of distinct birdcalls (e.g., cardinal, blue jay, and eaglet calls), each occurring for the duration of stimulus presentation

Participants. Twenty participants were recruited from the NU community and paid $15/hr for participation.

Materials. New prototype values were generated for this experiment. The prototype values for the three categories were (in order of hilliness, vegetation, time of day and weather; [0-1]) were: Alpha (0.442, 0.783, 0.753, 0.288), Bravo (0.748, 0.410, 0.877, 0.241), Charlie (0.449, 0.392, 0.683, 0.592). In addition, auditory cues in the form of three distinct birdcalls were embedded within 80% of total trials. Of these trials, 80% had auditory cues that were predictive of the categories. Overall, 64% of total trials contained predictive cues, 16% contained “False” cues, and 20% contained no auditory cues.

Procedure. In addition to the categorization response, participants were instructed to attend to the auditory elements of the videos. To motivate compliance, we embedded a ‘callsign’ in the auditory information on 10% of trials that participants were to listen for and make a separate response (press the keyboard space bar). Categorization trials were reorganized into blocks containing 75 trials, with 25 trials of each category present in each block. As in previous experiments, trials were pseudo-randomized by block so that trials belonging to a particular category would not appear more than three times consecutively. Short breaks continued to be provided after every 50 trials. The protocol again consisted of 450 total trials. The post-session interview was updated with a question added asking if and how participants used auditory features to make decisions during the task.

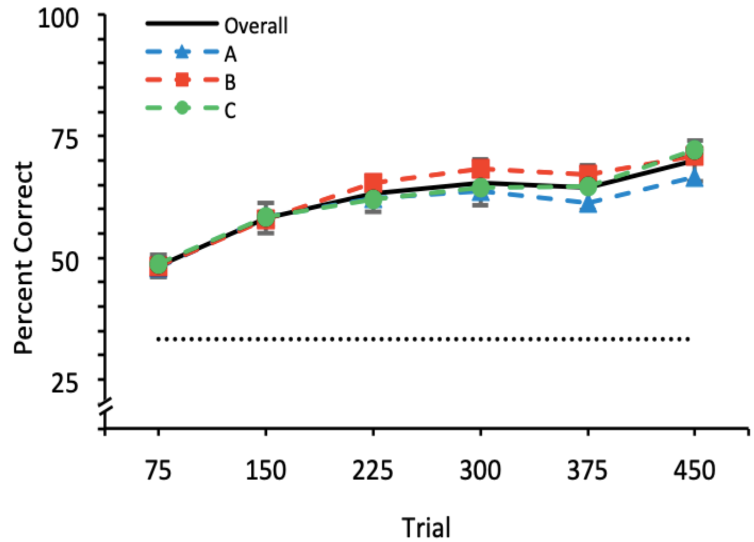

Figure 2.6: Overall and category accuracy in Experiment 4. 450 total trials were used in this task. Percent correct was determined by measuring performance across blocks of 75 trials. Participants showed learning over the course of the task. Participants showed similar levels of performance across all three categories. Overall performance was greater than chance (33%, represented by the dotted line) during the final block.

Results. Three participants were excluded for poor performance (< 75%) on the auditory 'catch' trials, suggesting lack of compliance with the task instructions. Participants' (n=17) performance (Figure 2.6) on the final block was 70% correct (SD 18%), significantly above chance, $t(19) = 8.6$, $p < 0.001$ and improved significantly from the first block (M = 48.5%, SD = 11%), $t(16) = 7.69$, $p < 0.001$. Participants appropriately responded to the auditory 'catch' trials, performing 94% correct (SD 6%) at identifying them, indicating they were attending to the auditory information. However, participants did not show sensitivity to the auditory cues overall, $F(2, 48) = 1.6$, $p=0.217$, although there was a trend for higher accuracy on the trials with predictive cues present. However, four participants reported awareness of the auditory cues' relationship to the correct category and used this information to improve their task performance, accounting entirely for the trend.

Discussion. Participants showed increased performance over the course of the task, learning all three categories at similar rates. However, the auditory cues did not have a measureable impact on performance across the group. For Experiment 5, the training protocol was extended for additional trials to provide more time for the implicit association between the auditory cue and the terrain category to strengthen.

2.5 Experiment 5

To provide additional time and training to build up implicit learning and the use of intuition in the category learning task, the protocol was doubled in length to two hour-long sessions occurring over two days. In addition, a new quantitative approach was developed to examine the relationship between the participants' verbal reports of strategy use and task performance. A strategy inference algorithm was devised to identify when participants' response choices were consistent or inconsistent with their explicit reports of strategy use. From this we could identify a subset of trials where the participants made categorization choices that did not appear to be based on explicit strategy and are more likely to be influence by implicit intuition.

Participants. Thirty-three participants were recruited from the NU community and paid $15/hr for participation.

Materials. Additional stimuli were generated (450, bringing the total to 900) based on the same prototype values used in Experiment 4. The auditory information was kept the same (overlaid on the new videos).

Procedure. The first 450 trials were presented during a single hour-long session and 450 more trials were presented in a second session approximately 24 hours after the first session. The post-session interview protocol was adjusted to ask participant how the importance of each dimension varied between categories (e.g., Hilliness could be highly important for recognizing trials belonging to Alpha while Weather could be more important in identifying Charlie trials). With this information from the participants, we could attempt to infer the strategy being used on each trial to determine what response was selected.

Explicit strategies were compared to actual choice behavior during the second session on a trial-by-trial basis. Using this comparison between verbally reported strategies and participants' choice behavior, subsets of trials were established: behavior consistent with reported strategies, behavior inconsistent with reported strategies, or behavior unaccounted for by reported strategies. Using this assessment, we determined the percentage of total trials belonging to each subset, as well as decision-making accuracy within each subset.

Results. Participants' performance (Figure 2.7) on the final block was 77% correct (SD 16%), significantly above chance, $t(32) = 16$, $p < 0.001$ and reliably higher than the first block (M = 51.6%, SD = 12%), $t(32) = 11.5$, $p < 0.001$. Participants were reliably more accurate on trials that contained the probabilistic auditory cues, $F(2, 96) = 4.877$, $p<0.01$ Interview responses revealed that some participants exhibited explicit awareness of the auditory cues. Excluding these ten participants from the data set revealed no differences in learning between cue conditions ($F(2, 66) = 0.113$, $p=0.893$), indicated little to no implicit acquisition of the auditory cues on overall task performance.

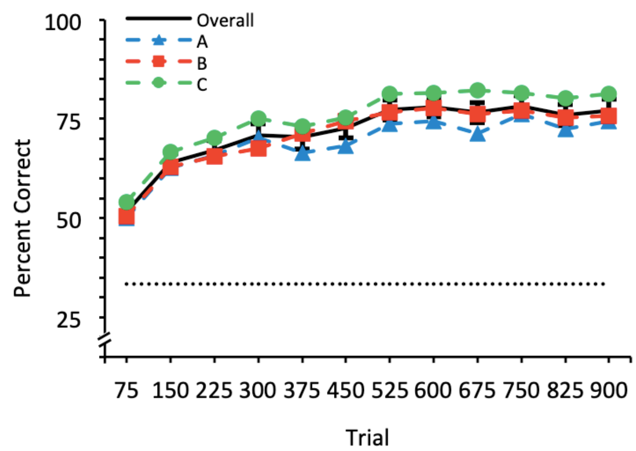

Figure 2.8: Overall and category accuracy in Experiment 5.1. 900 total trials were used in this task. Percent correct was determined by measuring performance across blocks of 75 trials. 450 trials were presented during a single session. Two sessions occurred approximately 24 hours apart. Participants showed learning over the course of the task. Participants showed similar levels of performance across all three categories. Overall performance was greater than chance (33%, represented by the dotted

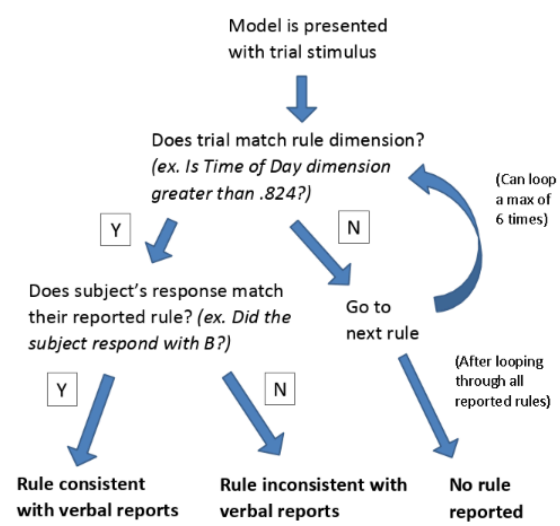

Figure 2.9: Algorithmic assessment was used to compare participants' choice behavior with reported strategies. This comparison was made on a trial-by-trial basis for second session trials. Trials were divided into subsets based on whether choice behavior was consistent with reported rules, inconsistent with

Using the newly expanded post-training interview protocol, we developed a novel method for characterizing the consistency of participants' performance with their post-session descriptions of their strategies (Figure 2.9). The dimensions given the highest importance rating by each participant were used in an algorithm to determine what category label would be applied to each stimulus if they meticulously followed the rules they described. This algorithmic approach was used to classify all the trials completed in the second day of learning, when their strategies should have been more consistent and stable, for the participants who did not report explicitly using the auditory cues (n=23). After classifying each answer given as either consistent with, inconsistent with, or unaccounted for by the reported explicit strategies, the accuracy of each of these types of responses was measured. On average 63% (SD 18%) of the participants' day 2 responses were consistent with the verbal strategies extracted from the post-experiment interview. Of the other responses, 23% (SD 13%) were inconsistent and 13% (SD 12.5%) had no rule that applied to the stimulus. Accuracy (Figure 2.10) was high for the rule-consistent trials and poor for the rule-inconsistent trials (M = 41%, SD = 26%) indicating that the rules reported were generally fairly accurate. On the subset of trials in which no rule could account for behavior, participants still showed greater choice accuracy in the subset of trials in which no rule could account for behavior (M = 67%, SD = 27%), exceeding chance, $t(22) = 5.88$, $p < 0.001$. These trials may reflect instances when the participants' abandoned or were unable to correctly apply their explicit rules but relied on a more intuitive hunch to make their response.

Discussion. Adding a second day of training with an additional 450 trials and a 24-hour consolidation period to the protocol did not appear to enhance implicit learning of the auditory cues. However, the additional performance data from the second day allowed for an analysis of participants' choice behavior contrasted with their verbally reported strategies. While the major proportion of their categorization responses appeared to depend on their explicit strategy, a notable subset of trials were identified in which participants either could not apply these rules or did not follow their own rules, but on these trials they still selected the correct category at better than chance rates. Success on these trials may have reflecting application of implicitly learned category information applied in a more intuitive way (i.e., not available to report after the session). Overall, the learning process on this task may reflect a complex combination of both explicitly learning and implicitly acquired category information. The challenge in designing a protocol to assess intuition use is to be better able to separate the impact of each of these types of knowledge and to be able to separately quantitatively estimate the effect sizes.

For Experiment 6, we attempted to encourage more use of implicit knowledge by a method of gradual occlusion of the visual features hypothesizing that this would lead to greater reliance on the probabilistic auditory (bird call) cues.

2.6 Experiment 6

To encourage more reliance on the auditory cues, we gradually reduced the visibility of the visual information over the course of training, making these parameters less available for the explicit strategies being developed by participants. Within the stimulus generation software, this was done using the weather and time of day parameters, using increasingly greater levels of weather cover and selecting times later in the day (reducing light). As these parameters could no longer be relevant to the category membership, we reconstructed the category prototypes using just the hills and vegetation parameters. The auditory cues probabilistically predicted the correct category label at the same rates as previous experiments.

Participants. Seven participants were recruited from the NU community and paid $15/hr for participation.

Materials. For this protocol, we created new category prototype values involving only two visual dimensions (topology and vegetation). The prototype values for the three categories were (in order of hilliness, then vegetation; [0-1]): Alpha (0.981, 0.697), Bravo (0.508, 0.538), Charlie (0.449, 0.392).

Procedure. Over the course of the task, occlusion increased steadily with each trial. Participants completed a single session of 450 trials. For this experiment, a short-open ended interview similar to the one used in Experiment 1 was administered in order to assess participants' general experience with the task.

Results. Participants' performance (Figure 2.11, Left Panel) on the final block (M = 57.14%, SD = 13.33%) was significantly above chance, $t(6) = 4.72$, $p < 0.01$. However, unlike in previous experiments, performance on the final block did not improve significantly compared to the first block (M = 45.71%, SD = 12.82%), $t(6) = 1.62$, $p = 0.16$. Participants showed no difference in performance across auditory cue conditions, $F(2, 18) = 0.009$, p=0.991, indicating they were not effectively encouraged to rely on the auditory cues as a result of the occlusion (Figure2.11, Right Panel). No participants reported explicitly learning to rely on the auditory cues.

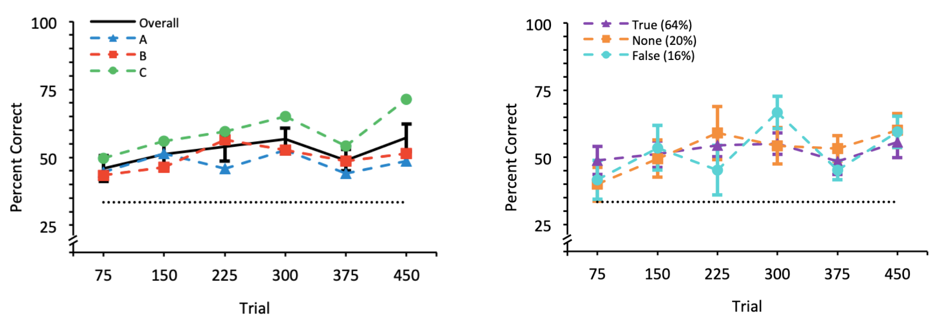

Figure 2.11. (Left) Overall and category accuracy in Experiment 7. Visual dimensions were gradually occluded during the task on a trial-by-trial basis. Overall performance was greater than chance (33%, represented by the dotted line) during the final block but did not improve over the course of the task. (Right) Performance did not differ across auditory cue conditions, even when the visual features were occluded.

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that occluding the visual dimensions and/or reducing the number of category-relevant dimension values interfered with participants' ability to learn the underlying category structure. In Experiment 7, the occlusion method was adjusted in an attempt to allow for better learning of the categories.

2.7 Experiment 7

For Experiment 7, occlusion increased gradually with sets of trials, as opposed to each trial, and the gradient was increased in order to make the occlusion more salient at the end of the training protocol. In addition, non-occluded trials were included on a subset of trials towards the end of the protocol to verify that participants had learned and still remembered the key visual features predictive of category membership.

Participants. Seven participants were recruited from the NU community and paid $15/hr for participation.

Materials. New prototype values were generated for Charlie (0.882, 0.207) in order to balance category discriminability. The Alpha and Bravo categories were the same as Experiment 6.

Procedure. We altered the occlusion gradient so that occlusion went from non-occluded early in learning to more substantial visual cover by the end and the occlusion levels changed over sets of trials rather than individual trials. Trials -1-150, were not occluded at all to allow for learning of the visual categories, trials 151-200 was somewhat occluded, and trials 201-450 were maximally occluded but 20% of trials (randomly interspersed) in this subset were non-occluded to assess knowledge of the visual category parameters later in learning. A short, open-ended interview was once again administered in order to assess participants' general experience with the task.

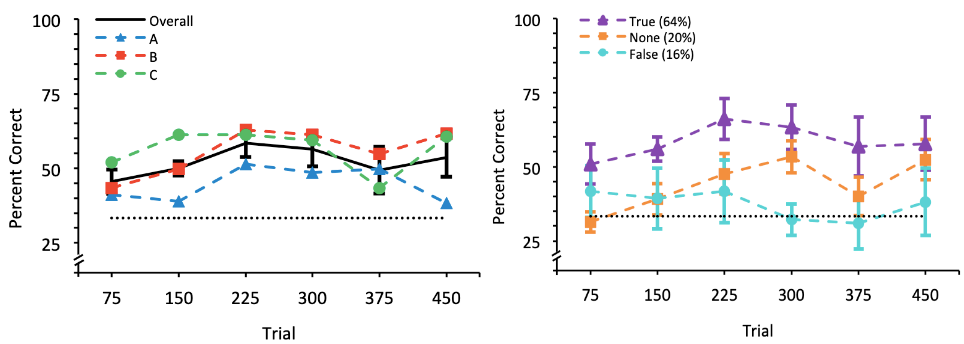

Figure 2.12. (Left) Overall and category accuracy in Experiment 7. Visual dimensions were non-occluded from trials 1-150, moderately occluded during from trials 151-200, and maximally occluded from trials 201-450. Overall performance was greater than chance (33%, represented by the dotted line) during the final block but did not improve over the course of the task. (Right) Performance was strongly affected by the auditory cue condition, but all participants explicitly mentioned using auditory cues in verbal reports

Results. Participants' performance (Figure 2.12) on the final block was 54% correct (SD=17%), significantly above chance, $t(6) = 3.92$, $p < 0.05$. Performance on the final block was not significantly better than the first block (M = 45%, SD = 11%), $t(6) = 1.49$, $p = 0.19$. Post-session interviews revealed that all participants explicitly learned, or were at least attentive to, the auditory cues, underlying the small differences between cue conditions ($F(2, 18) = 2.842$, $p=0.085$).

Discussion. Because all participants relied on explicit strategies involving auditory cues during the task, we could not assess the role of implicit learning of the auditory cues in Experiment 7. In addition, participants still showed low levels of overall learning, indicating that the occlusion paradigm did not encourage implicit learning of the auditory cues and instead reduced the overall difficulty of the task.

2.8 General Discussion

Across experiments, participants generally showed reliable learning of complex categories based on four underlying parameters that determined the visual characteristics of procedurally generated terrain stimuli. This learning was accomplished by participants without any information about the underlying category structure being provided explicitly. All task learning was done through trial-and-error with feedback, providing participants with the opportunity to both explicitly discover categorization strategies or gradually build up implicit knowledge of the task. With this approach, we were able to successfully develop a new laboratory learning task that used stimuli related to operationally-relevant training. In this new protocol, we were able to characterize both the rate of learning and develop methodological tools for quantifying the explicit task strategies learned by participants during the training session.

The Terrain Categorization task developed here improves on current techniques for laboratory studies of category learning by using more relevant, complex stimuli, but still maintaining a well-controlled underlying mathematical structure. Critical to the task development was the interdisciplinary effort with our collaborators at Charles River Analytics to bring sophisticated technological solutions to procedural content generation (the stimulus generation software) together with modern cognitive neuroscience-based scientific approaches. Well-controlled experimental conditions can be successfully combined with operationally-relevant content domains to support quantitative measures of learning.

Our ability to measure robust implicit learning on the new category learning task during the first 1-2 hours of training was not as effective as hoped. The complexity of the task allowed for substantial explicit learning that tended to be the main driver of decision-making performance. Expert intuition outside the laboratory is typically expected to develop of many hours (even months or years) of experience. While implicit learning paradigms are often able to identify measurable signals of the beginning of this process within short laboratory sessions of only an hour or two, this may depend on the peculiar and artificial nature of the stimuli used in those experiments. In general, the stimuli used in implicit learning studies are unfamiliar and this is used to help hide the underlying statistical structure of the task from explicit discovery. However, even within the literature of experimental studies of implicit learning, the challenge of reducing explicit discovery by undergraduate participants is a long-standing one (Destrebecqz & Cleermans, 2001; Reber 2013).

Three approaches were tested here to attempt to quantify robust contributions from implicit learning on the Terrain Categorization task. First, we carried out extended post-learning interviews to characterize the amount of explicit task knowledge discovered by participants during learning. In some prior research, the discrepancy between performance and reportable knowledge indicates a robust effect of implicit learning (e.g., A.S. Reber, 1967). Second, we embedded additional, probabilistic information into the auditory aspect of the stimuli. Because the focus of explicit discovery was on the visual features the lack of attention directed to the auditory cues might have allowed more influence from implicit learning (Voss & Paller, 2009). In addition, probabilistic stimuli have been found to produce better implicit learning by making explicit discovery less likely (Song, Howard & Howard, 2007). However, participants continued to primarily rely on explicit strategies for learning the terrain categories. Because implicit and explicit learning approaches are often found to operate competitively (Ashby et al. 1998; Poldrack & Packard, 2003; Nomura & Reber, 2012; Reuveni & Reber, in preparation) it may have been the case that any implicit learning that was occurring was masked or inhibited by the reliance on explicit knowledge. Third, we attempted in Experiments 6 and 7 to use a gradual occlusion technique to shift participants from an explicit to more implicit strategies. This technique did not successfully discourage explicit learning but may still have some promise in paradigms with more extended training protocols.

It is likely that quantification of the influence on implicit learning on intuitive decision making will require training protocols that extend for more hours than in the paradigms used here. Over tens of hours or more, participants will tend to automate learning and become more habitual in performance. This form of learning depends on the same underlying neural mechanisms as implicit learning (Reber, 2013) and thus, we would expect to see increasingly rapid, effortless and intuitive cognitive processes with more training. However, since implicit learning phenomena are often found to be highly specific to the task being practiced (inflexible in application; Sanchez, Yarnik & Reber, 2015), examination of implicit learning in longer domains should generally be undertaken with even more directly relevant skill domains. Thus, our recommendation would be for future research characterizing the impact of implicit learning on skill development to be done directly using operationally relevant training domains, but using the methodological tools of laboratory studies of learning and memory.

List of publications and presentations

Manuscripts

1. Squire, P., Cohn, J., Nicholson, D., Nolan M., Reber, P.J., Oudiette, D, Niehaus, J., Geyer, A., & O'Neill, L. (2014). Towards enhancing intuitive decision making through implicit learning. Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC) 2014.
2. Hechtman, L. A. (2015). The relationship between executive function and creative cognition: A behavioral and neural investigation. ProQuest Digital Dissertations (ID: 3705263).
3. Smith, M.K., Reuveni, B. Cohen, M.S., Grabowecky, M. & Reber, P.J. (2017). Developing a naturalistic categorization task for testing intuitive decision making. Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC) 2017.
4. Cohen, M.S., Cheng, L.Y., Paller, K.A., Reber, P.J. (in press). Separate memory-enhancing effects of reward and strategic encoding. *Journal of Cognitive Neuroscience.*
5. Reuveni, B. & Reber, P.J. (in preparation). PINNACLE 2.0: An Updated Theoretical Computational Model of Visual Category Learning.
6. Zabelina, D. L., Hechtman, L. A., Saporta, A., Grunewald, K., & Beeman, M. (in preparation). Creativity and attention: fMRI evidence for reduced perceptual integration as the mechanism for focused attention in divergent thinkers.

Conference Presentations

1. Zabelina, D. L. (2015). Different types of attention for divergent thinkers and creative achievers: fMRI evidence. 'Neuroscience of Creativity' Symposium Chair. Oral presentation at the 123th American Psychological Association Annual Convention. Toronto, Canada.
2. Zabelina, D. L. (2015). Flexible or "leaky" attention in creative people? Distinct patterns of attention for different types of creative thinking. Behavioural and Clinical Neuroscience Seminar. University of Cambridge, Cambridge, UK.
3. Zabelina, D. L. (2015). Are creative people more distractible? Behavioral, EEG, & fMRI evidence. Psychology Department, University of Surrey. Guilford, UK.
4. Reuveni, B. & Reber, P. J., (2016). *Dissociating Explicit from Implicit Strategies In Two-Dimensional Category Learning.* Cognitive Neuroscience Society, New York, New York.
5. Cohen, M.S., Cheng, L.Y., Paller, K.A., Reber, P.J. (2016). *High value leads to improved explicit recollection, but reduced implicit memory, when learning kaleidoscope images.* Poster presented at the 23rd annual meeting of the Cognitive Neuroscience Society, New York, NY.

6. Cohen, M.S., Cheng, L.Y., Haque, K., Paller, K.A., Reber, P.J. (2016). *Brain regions associated with value- driven encoding of novel kaleidoscope images.* Poster presented at the 46th annual meeting of the Society for Neuroscience, San Diego, CA.
7. Zabelina, D. L. (2016). "Leaky" attention and creativity: Behavioral, EEG, and fMRI evidence. "Making connections: Intersection of liberal arts, brain research explored in new lecture series." Lawrence University. Appleton, WI.
8. Cohen, M.S., Cheng, L.Y., Paller, K.A., Reber, P.J. (2017). *Lateral occipital complex activation associated with response confidence during forced-choice recognition of novel abstract kaleidoscope images.* Poster presented at the 24th annual meeting of the Cognitive Neuroscience Society, San Francisco, CA.
9. Reuveni, B. & Reber, P. J., (2017). *PINNACLE: A Theoretical Process Model of Human Visual Category Learning.* Cognitive Neuroscience Society, San Francisco, California.
10. Cohen, M.S., Cheng, L.Y., Paller, K.A., Reber, P.J. (2018). *Reward-related brain activity during successful memory encoding.* Nanosymposium talk given at the 48th annual meeting of the Society for Neuroscience, San Diego, CA.
11. Cohen, M.S., Reber, P.J. (2018). *Expectations about type of recognition test affects alignment of retrospective confidence judgments with accuracy.* Poster presented at the 59th annual meeting of the Psychonomic Society, New Orleans, LA.
12. Reuveni, B., Feinstein, B., Reber, P. J., (2018). *Modeling Memory Systems Interactions During the Development of Decision-Making Expertise.* Society for Neuroscience. San Diego, California.
13. Feinstein, B., Reber, P.J. (2018). *Explicit and implicit strategy diagnosis from verbal reports following category learning.* Society for Mathematical Psychology, Madison, WI.
14. Reuveni, B. & Reber, P. J., (2018). *Cognitive Computational Model Used to Manipulate Strategy Use During Visual Category Learning.* Society for Mathematical Psychology. Madison, Wisconsin.
    Conference Award for best Poster Presentation.

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14. ABSTRACT
This report summarizes a set of research studies supported by a Basic Research Challenge to examine how implicit learning research can be used to accelerate the development of expert intuition in training. The foundational basic science approach to this work is that implicit learning (Reber, 2013) reflects a separate type of learning and memory which accumulates through experience outside of awareness and influences behavior through intuition. The main goal of the research project described here is to examine how to take capitalize on these laboratory paradigms to accelerate the development of operationally relevant intuitive decision making in practical contexts.

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